# Impacts of Crew Training Quality Evaluation System Based on GA-BP Algorithm on Transportation Safety

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*Nowadays, shipping safety accidents occur frequently. Crew education and training can reduce shipping accidents to a certain extent. However, currently, there is no established method to investigate the specific relationship between crew education and training and shipping safety. To solve the problem, the study utilizes a genetic algorithm (GA) with strong global search capability and scalability to improve the low learning efficiency, slow convergence speed, and local optimal problems in the back propagation (BP) neural network, resulting in the genetic algorithm-back propagation (GA-BP) algorithm. The relevant indicators in crew education and training are input into the algorithm to predict the safety of shipping. The performance comparison experiments of GA-BP, particle swarm optimization-back propagation algorithm particle swarm optimization-back propagation (APSO-BP) algorithm and traditional BP neural network are carried out. The experimental outcomes showed that the hit rate of GA-BP was 90%, and its mean absolute error was 0.00152, the mean square error was 0.00323, and maximum absolute percentage error was 5.3%, which were better than APSO-BP and traditional BP neural network. In addition, in the empirical analysis, the output outcomes of psychological quality and adaptability were 0.92 and 0.93, respectively. The above outcomes show that the optimized GA-BP has better predictive performance, and the specific effects of psychological quality and adaptability in crew education and training on the safety of shipping can be obtained. This method not only provides data support for the improvement of crew education and training methods, but also provides a new method for predicting shipping safety*

*Povzetek: Opisan je vpliv sistema ocenjevanja kakovosti usposabljanja posadke, ki temelji na algoritmu GA-BP, na varnost v transportu. Rezultati kažejo, da GA-BP izboljša napovedno točnost z večjo natančnostjo in manjšimi napakami v primerjavi z drugimi metodami, kar prispeva k izboljšanju metod usposabljanja posadke in večji varnosti v pomorstvu.*

## 1 Introduction

With the frequent occurrence of ship losses and pollution accidents in the maritime field, the causes of accidents have attracted the attention of relevant organizations [1]. After investigation by relevant organizations, it was found that 80% of the accidents were caused by humans. Therefore, the quality of crew members has attracted widespread attention from the international community [2]. The quality of the crew depends largely on the education and training of the crew, so the quality of the education and training for crew members has a significant impact on shipping safety [3]. However, at present, there is a lack of quality evaluation models for crew education and training. Therefore, it is necessary to explore a model that can accurately evaluate the quality of crew education and training. With the rapid development of neural network, back propagation (BP) neural network is widely used in various fields [4]. However, the traditional BP network has slow convergence speed and low accuracy. The genetic algorithm (GA) can be used for BP neural network to solve slow convergence speed [5]. Therefore, the research combines BP and GA to form a GA-BP model, and applies the GA-BP model to shipping safety prediction. Through this model, the evaluation indicators of the quality of crew education and training are evaluated to predict the shipping safety, and improve the dilemma of lacking an evaluation system for the quality of crew education and training. It is expected to improve relevant indicators through prediction results to enhance shipping safety.

## 2 Literature review

In recent years, with the rapid development of BP neural network, its application in many fields is deepening. Aiming at the low container transportation efficiency, Zhu W et al. proposed a container inter-modal transportation evaluation model based on BP neural network. The experimental outcomes showed that the evaluation effect of the model was accurate, which effectively improved the efficiency of container inter-modal transportation [6]. To solve the inaccurate digital currency risk prediction methods, Shao et al. proposed an investment risk model that combined information entropy and BP neural network. The model could change the weight to carry out weighted scoring of digital currency to increase the accuracy. The results showed that the model could accurately predict the development prospects of digital currency, effectively helping investors avoid investment risks [7]. Liu et al. designed a BP neural network model for thermal error calculation of five-axis machining centers. The relationship between radial error and axial error during five-axis machining was calculated. The prediction accuracy of the error was high, which was more effective in practical applications [8]. Aiming at the insufficient urban evaluation model, Xi et al. proposed a new model by combining BP neural network and analytic hierarchy process. The separation index of urban solid waste was established, which was applied to the classification and evaluation of urban domestic waste. The evaluation outcomes showed that the model could effectively predict the urban garbage classification ability in the actual environment, providing a new way for urban evaluation to improve related capabilities [9]. Zhou et al. proposed a BP neural network based on monotonic constraints to solve the difficulty in controlling the phosphorus content at the end of the dephosphorization converter. The model was empirically analyzed. Phosphorus content in algae provided a control aid [10].

In addition, there are more methods applied in the field of shipping safety. In order to improve the shipping safety, Zhou et al. proposed a USV decision support model to improve the accuracy of collision avoidance decisions. The empirical test of the model showed that the model judgment in the collision stage was accurate, and the ship could take direct and effective collision avoidance measures, which effectively improved the safety of shipping [11]. Nosov et al. proposed a model based on navigation decision tree principle to address the insufficient safety of maritime navigation. A new type of ship control system was developed based on the prediction results of the model. The test results showed that it reduced the probability of critical situations by 18-54%, effectively reducing emergency risks [12]. To solve the new challenges related to navigation safety caused by the low maneuverability of ships and the increasingly dense maritime traffic, Shilov proposed an operation method aimed at designing a navigation safety recommendation system. The recommendation system operation method updated the feedback of the system knowledge base. By comparing the knowledge before and after, the security of navigation was effectively improved [13]. Hasanspahi et al. proposed a risk assessment matrix based on the grounding risk assessment combined with factors such as ship speed, hull quality, and loading conditions in order to solve the problem that oil tankers were easily grounded in narrow waterways and other specific navigation areas. The matrix could effectively evaluate the navigation safety of oil tankers in narrow waterways, which had important practical significance [14]. The results and limitations of the above research content are shown in Table 1.

Table 1: Results and limitations of the research content

| Reference | Methodology | Model | Application | Key findings | Limitation |
|---|---|---|---|---|---|
| Zhu et al. [6] | BP neural network | Transport accurate evaluation model | Container transport | Improve the efficiency of container inter-modal transportation | Limited to container shipping only |
| Shao et al. [7] | Joint information entropy and BP neural network | Investment risk model | Digital currency risk prediction | Accurately predict the development prospects of digital currency | There is greater uncertainty |
| Liu et al. [8] | BP neural network | BP neural network model for thermal error calculation | Five-axis machining center thermal error calculation | Improve the accuracy of error prediction | Weak anti-interferen ce |
| Xi et al. [9] | BP neural network and hierarchical analysis | Evaluation model of household waste classification | Urban garbage classification evaluation | Accurately predict the garbage classification ability of cities in the actual environment | Large calculation time complexity |
| Zhou et al. [10] | Monotonically constrained, BP neural network | Phosphorus content control model | Control of phosphorus content in | Accurate control of the phosphorus content | Only for phosphorus content |

| | | | | | |
|---|---|---|---|---|---|
| | | | dephosphorization converter | | control |
| Zhou et al. [11] | USV | Decision support model | Shipping safety, collision avoidance | Improve the shipping safety | Information is difficult to obtain |
| Nosov et al. [12] | Navigation of the decision tree principle | New ship control system | Maritime navigation safety | Effectively reduce the risk of emergency situations | It's difficult to operate |
| Shilov [13] | Navigation security | Safety recommended system operation method | Navigation safety in dense maritime traffic | Improve navigation safety | Information overload |
| Hasanspahi et al. [14] | Stranded risk assessment | Risk assessment matrix | Navigation safety of oil tankers in narrow waterways | Effectively assess navigation safety in narrow waterways | Subjectivity and uncertainty |

The above research shows that BP neural network has been widely used in many fields. Methods applied to the field of shipping safety are also emerging one after another. However, the research on applying BP neural network algorithm to the field of shipping safety is still relatively lacking. Therefore, this study applies BP neural network to predict shipping safety risks, and improves the BP neural network through GA. Through a comprehensive evaluation, it is expected to help identify deficiencies in crew training and make improvements to improve shipping safety.

# 3 Evaluation system of crew education and training quality based on BP neural network

## 3.1 BP neural network and its improved algorithm

With the in-depth understanding of neural network theory, more neural networks are applied in real life. Currently, BP neural network is one of the most successful and common neural networks [15]. Its structure is similar to a multi-layer perceptron, and its principle is to forward the input signal, and then adjust the weights by back propagating the error signal, thereby reducing the model error [16]. The main function of BP neural network is to classify samples and predict outcomes, etc. The traditional structure diagram of the BP neural network is shown in Figure 1 [17].

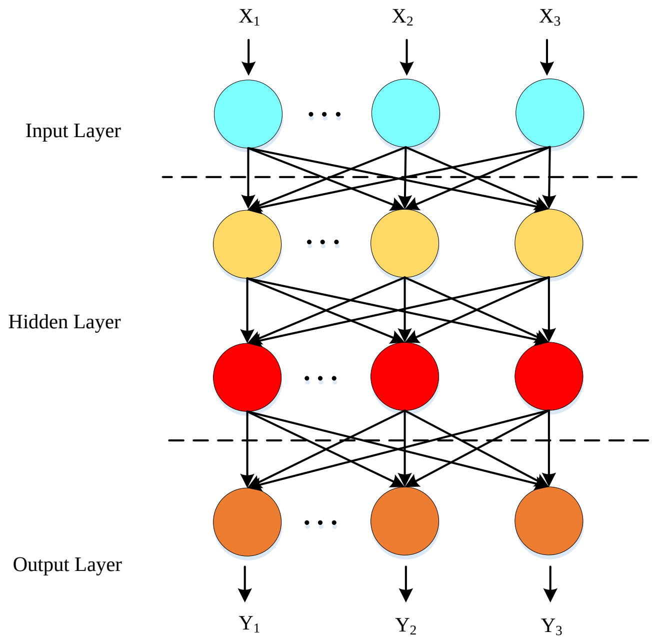


Figure 1: Structure diagram of traditional BP neural network

As shown in Figure 1, the structure is the traditional BP neural network. $x_n(n=1,2,\cdots,k)$ is the input value, and $y_n(n=1,2,\cdots,k)$ is the output value. $N_{k-1}$ denotes the number of nodes of the neurons. In the forward propagation of the neural network, each neuron will summarize the weighted information, and its expression is shown in equation (1).

$$net_{kl}=\sum_{j=1}^{N_{k-1}}O_{(k-1)j}\cdot W_{(k-1)jl} \quad (1)$$

In equation (1), $net_{kl}$ represents the $k$ aggregated weighted information of the $O_{(k-1)j}$ -th neuron in the $j$ -th layer . $l$ represents the $k-1$ output value of the $k-1$ -th neuron in the $k$ -th layer $j$ . $W_{(k-1)jl}$ is the connection weight from the $j$ -th neuron in the $j$ -th layer to the $k$ -th neuron in the $j$ -th layer. In the forward propagation, in addition to summarizing the weighted information, each neuron will also pass the summed information through the activation function and output, and its expression is shown in equation (2).

$$O_{kl}=f_s(net_{kl})=\frac{1}{1-\exp[-(net_{kl}-\theta_{kl})]} \quad (2)$$

In equation (2) $\theta_{kl}$ represents the $k$ threshold of the first neuron in the $l$ -th layer. In the BP neural network, the mean square error is selected as the index to judge its performance. The algorithm back propagates the difference between the output outcome $y_l$ and the expected output $d_l$ to correct the weights of neurons in each layer. The expression of the objective function is shown in equation (3).

$$E=\frac{1}{2}\sum_l(d_l-y_l)^2 \quad (3)$$

In equation (3) $d_l-y_l$ represents the difference between the output outcome and the expected output, that is, the back propagated error signal. The BP network uses the gradient descent method to correct the neuron weights, and its expression is shown in equation (4).

$$\Delta W_{klj}=-\eta\frac{\partial E}{\partial w_{klj}} \quad (4)$$

In equation (4), $\eta$ represents the learning step size. $\Delta W_{klj}$ indicates the weight correction between the $j$ neuron and the $k$ neuron in the $l$ layer. The relationship $\Delta W_{klj}$ between it and the neuron output is calculated using partial derivatives, and its specific expression is shown in equation (5).

$$\Delta W_{klj}=-\eta\frac{\partial E}{\partial w_{klj}}=-\eta\frac{\partial E}{\partial net_{(k+1)j}}\cdot\frac{\partial net_{(k+1)j}}{\partial w_{klj}}=\eta\delta_{kj}\frac{\partial net_{(k+1)j}}{\partial w_{klj}} \quad (5)$$

In equation (5) $\delta_{kj}$ is the weight correction value between the $k+1$ and $j$ neurons. $\delta_{kj}=-\frac{\partial E}{\partial net_{(k+1)j}}$. The first part of equation (5) is solved, and the solution process is shown in equation (6).

$$\frac{\partial net_{(k+1)j}}{\partial w_{klj}} = \frac{\partial}{\partial w_{klj}} \left(\sum_{h=1}^{N_k} O_{kh} \cdot W_{khj}\right) = O_{kl} \tag{6}$$

In equation (6) $N_k$ represents the number of nodes of the $k$ neurons in the first layer. In the right side of equation (6), $O_{kl}$ represents the output value of the $k$ neuron in the $l$ layer. Equation (7) can be obtained from equation (5) and (6).

$$\Delta W_{klj} = -\eta \frac{\partial E}{\partial w_{klj}} = -\eta \delta_{kj} O_{kl} \tag{7}$$

In equation (7), $\delta_{kj}$ is shown in equation (8).

$$\delta_{kj} = -\frac{\partial E}{\partial net_{(k+1)j}} = -\frac{\partial E}{\partial O_{(k+1)j}} \cdot \frac{\partial O_{(k+1)j}}{\partial net_{(k+1)j}} \tag{8}$$

In equation (8) $\frac{\partial O_{(k+1)j}}{\partial net_{(k+1)j}} = f'(net_{(k+1)j})$. The expression for derivation is shown in equation (9).

$$f'(x) = \frac{e^{-(x-\theta)}}{[1+e^{-(x-\theta)}]^2} = f(x)[1-f(x)] \tag{9}$$

The calculation process shown in equation (10) can be obtained by equation (9).

$$\frac{\partial O_{(k+1)j}}{\partial net_{(k+1)j}} = f'(net_{(k+1)j}) = f(net_{(k+1)j})(1-f) = O_{(k+1)j}(1-O_{(k+1)j}) \tag{10}$$

When $O_{(k+1)l}$ is a hidden layer node, the expression of $\frac{\partial E}{\partial net_{(k+1)j}}$ and $\delta_{kj}$ is shown in equation (11).

$$\begin{cases} \dfrac{\partial E}{\partial net_{(k+1)j}} = \sum\limits_{h=1}^{N_{k+2}} \dfrac{\partial E}{\partial net_{(k+2)h}} \cdot \dfrac{\partial net_{(k+2)h}}{\partial O} = -\sum\limits_{h=1}^{N_{k+2}} \delta_{(k+1)h} w_{(k+1)jh} \\ \delta_{kj} = O_{(k+1)j}(1-O_{(k+1)j}) \sum\limits_{h=1}^{N_{k+2}} \delta_{(k+1)h} w_{(k+1)jh} \end{cases} \tag{11}$$

When $O_{(k+1)l}$ is an output layer node, the expression of $\frac{\partial E}{\partial O_{(k+1)j}}$ and $\delta_{kj}$ is shown in equation (12).

$$\begin{cases} \dfrac{\partial E}{\partial O_{(k+1)j}} = y_j - d_j \\ \delta_{kj} = (d_j - y_j) O_{(k+1)j}(1-O_{(k+1)}) = (d_j - O_{mj}) O_{mj}(1-O_{mj}) \end{cases} \tag{12}$$

Through the calculation, the weight adjustment equation of the algorithm can be obtained, as shown in equation (13).

$$\Delta W_{klj} = \begin{cases} \eta(d_j - y_j) y_j (1-y_j) O_{kl} & \text{i+1 layer is the output layer} \\ \eta O_{(k+1)j}(1-O_{(k+1)j}) \cdot \left(\sum\limits_{h=1}^{N_{k+2}} \delta_{(k+1)h} \cdot w_{(k+1)jh}\right) O_{kl} & \text{i+1 layer is a hidden layer} \end{cases} \tag{13}$$

Similarly, the threshold adjustment equation of the BP neural network can be obtained, as shown in equation (14).

$$\Delta \theta_{kj} = \begin{cases} \eta(d_j - y_j) y_j (1-y_j) & \text{i+1 layer is the output layer} \\ \eta O_{(k+1)j}(1-O_{(k+1)j}) \cdot \left(\sum\limits_{h=1}^{N_{k+2}} \delta_{(k+1)h} \cdot w_{(k+1)jh}\right) & \text{i+1 layer is a hidden layer} \end{cases} \tag{14}$$

Although the current BP neural network has extensive applications, it still has many shortcomings, such as long training time and easy to fall into local minima [18]. Therefore, the research uses GA to optimize the BP neural network. The GA can optimize the weights and thresholds of the BP network by using its strong search ability to increase its convergence speed and optimize its performance [19]. The optimization process of the GA is actually to iterate the individuals in the algorithm, judge the fitness of the individuals after iteration, and select the individual with the best fitness for output [20]. The specific process of the GA after optimization is shown in Figure 2.

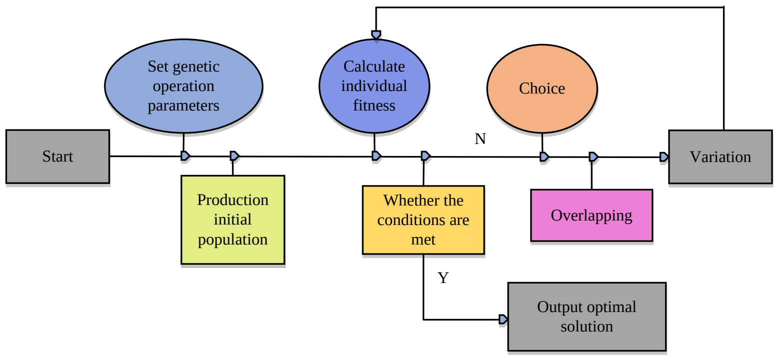


Figure 2: The specific process diagram of the genetic algorithm

In Figure 2, the first step is to initialize the population, generate different individuals, and then use the fitness function to judge the fitness of the individual to determine its adaptability to the environment. Individuals with better environmental fitness are selected to enter the next generation for iteration, so that the algorithm can gradually obtain the optimal solution in the iterative process. Individuals are selected from the population to perform crossover and mutation operations according to the corresponding probability to generate new individuals and enter the next generation. Finally, whether the output outcomes meet the requirements is determined. If they meet the requirements, the algorithm ends and the optimal individual is output. Otherwise, the process is returned to continue execution. The preprocessing method of the GA-BP is generally to normalize the data, and map the data to the [0,1] interval, thus increasing the convergence speed of the algorithm. The normalization is calculated, as described in equation (15).

$$y = (x - \min) / (\max - \min) \qquad (15)$$

In equation (15) $x$ indicates the input value. $\min$ indicates the minimum value in the input value. $\max$ indicates the maximum value in the input value. Equation (15) converts the data into intervals [0,1] to reduce the training time of the algorithm and improve its computational efficiency. The shipping safety is very important, which is of great practical significance to accurately predict its safety. The GA-BP algorithm obtained by optimizing the BP neural network through the GA has better prediction performance. Therefore, using the GA-BP to predict the shipping safety can improve the prediction accuracy. The specific prediction flowchart is shown in Figure 3.

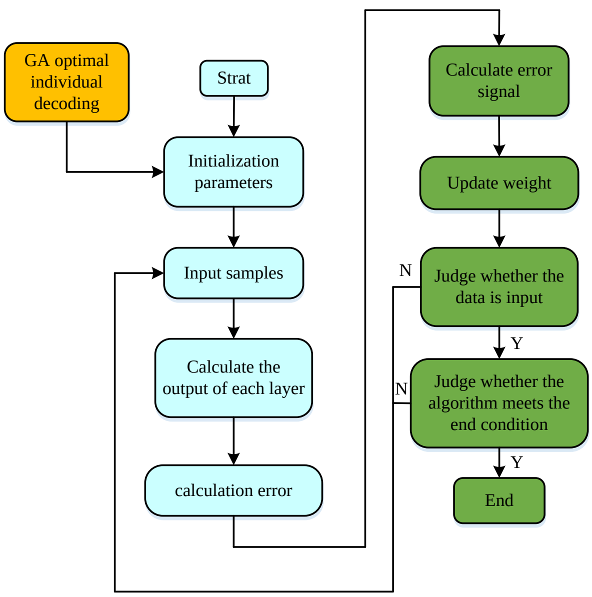


Figure 3: Flowchart of GA-BP prediction algorithm

As shown in Figure 3, the specific steps of the GA-BP prediction algorithm are as follows. Firstly, the structure of the neural network is determined in combination with the sample set in practical applications. Then the parameters of the BP are initialized by using the optimal individual code output by GA. The next step is to calculate the output of each level of the neural network through the input samples, and compare the actual output outcomes with the expected output outcomes to obtain the error. The error is converted into an error signal and back propagated, with each neuron weighted and updated. Finally, it is judged whether the data input is completed. After the input is completed, whether the algorithm ends is judged. If the end condition is met, the algorithm ends. Otherwise, the output of each level is calculated from the input sample and the algorithm is restarted until the end condition is reached. The GA-BP can solve the problem that the training falls into the local minimum due to the large difference in initial values of the BP, greatly strengthening the performance of the BP, and better predicting the shipping safety.

## 3.2 Construction of quality evaluation System for crew education and training

In the crew education and training, there are many factors that affect the shipping safety more or less. To predict the shipping safety, it is necessary to build an evaluation index system for the education and training system of seafarers, that is, to analyze the training system and find a suitable index system to comprehensively evaluate it. On the basis of analyzing the factors that affect the overall security of the system, a scientific and reasonable evaluation system is established. For the composition of the system, it can be represented by equation (16).

$$S = (E, R) \tag{16}$$

Equation (16) $S$ represents the system. $E$ represents the element set of the system. $R$ represents the relationship between the elements in the system. Evaluating the system from different perspectives will generate different evaluation indicators. In the research on the impact of the crew education and training system on shipping safety, the evaluation indicators for the impact of the crew education and training system on shipping safety are shown in Table 2.

Table 2: Evaluation indicators for the impact of crew education and training systems on shipping safety

| Evaluation system | Primary index | Indicator code | Indicator code |
|---|---|---|---|
| Shipping safety evaluation system | Crew factor | Family environment background | Z1 |
| | | education level | Z2 |
| | | Psychological quality | Z3 |
| | | Physical quality | Z4 |
| | | Adaptability | Z5 |
| | Education and training institutions | Meet the requirements of the competent authority | Z6 |
| | | Teacher level | Z7 |
| | | Condition of facilities and equipment | Z8 |
| | | Training scale | Z9 |
| | | Training cycle | Z10 |
| | | Operation of quality system | Z11 |
| | | market demand | Z12 |
| | | Information integration processing | Z13 |
| | | Crew entry standard settings | Z14 |
| | Shipping company | Feedback of new ship technology | Z15 |
| | | Demand for production safety | Z16 |
| | | Crew management level | Z17 |
| | Competent authority | Evaluation of crew training effect | Z18 |
| | | Daily supervision service | Z19 |

From Table 2, the research selects evaluation indicators from four major directions: crew factors, education and training institutions, shipping companies, and competent authorities. Among the above evaluation indicators, because the background factors of the crew have already occurred, it is difficult to change and plays an important part in crew training, so the study selects them as the evaluation indicators. The crew factors are further subdivided into five specific evaluation indicators: crew family environment, cultural level, psychological quality, physical quality, and adaptability. In addition to crew factors, another major category of evaluation indicators that has a significant impact on the training quality of the training system is education and training institutions. For education and training institutions, they are the main body of crew training, which play an important role in the crew training. The indicators of education and training institutions are mainly divided into nine aspects, namely meeting the objective requirements of the competent authority, the number of teachers for education and training, the condition of training equipment and facilities, training scale, training cycle, the operation of the training quality system, market demand, information integration and processing, and crew entry standard. The other two categories of evaluation indicators are shipping companies and competent authorities. Shipping company indicators are further subdivided into information feedback on new ship technologies, demand for production and safety, and internal management. These three evaluation indicators are mainly conducted on land. The indicators of the competent authority are divided into crew training effects and daily supervision services. These two evaluation indicators have the function of testing the outcomes and process of crew training. The effectiveness of crew training can be comprehensively evaluated through 19 evaluation indicators. The training effect of crew members has a significant impact on shipping safety. Therefore, based on the 19 evaluation indexes, this study establishes a quality evaluation system model for crew safety education and training based on GA-BP. The transportation safety model based on GA-BP algorithm is shown in Figure 4.

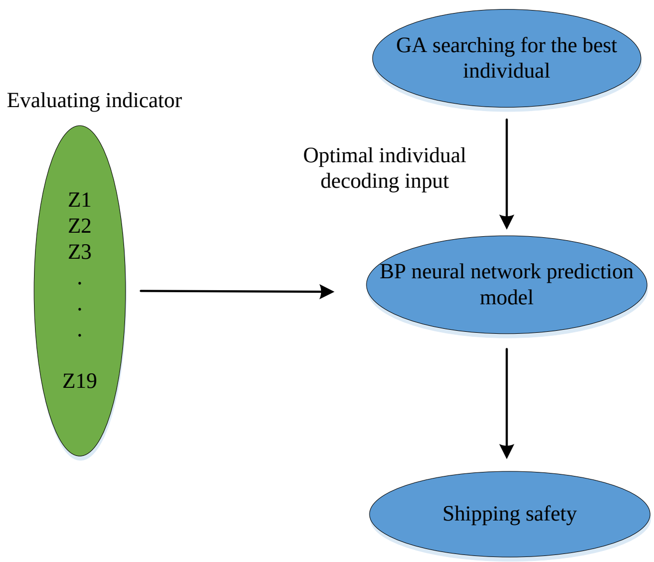


Figure 4: Schematic diagram of GA-BP algorithm for predicting shipping safety

As shown in Figure 4, GA is used to find the optimal individual sample in the sample set. Then the sample code is used to initialize the parameters of the BP neural network. The 19 evaluation indicators of the crew education and training system are input into the BP after parameter initialization. The positive and negative propagation of the BP neural network is used to adjust the weights and thresholds of each neuron until the algorithm is finally completed. By inputting 19 evaluation indicators from the crew education and training system to predict shipping safety, the impact of crew education and training quality on shipping safety can be determined. Because the 19 evaluation indicators of the crew education and training system can also evaluate the quality of crew education and training, the relationship between the quality of crew education and training and shipping safety can be analyzed.

# 4 Algorithm performance comparison and model empirical analysis

The parameters in the experiment are set as follows. The population size of the GA is set to 100. The number of iterations is set to 500. The crossover probability is set to 0.5 and the variation probability is 0.005. The learning rate in the BP neural network is set to 0.005, and the momentum coefficient is set to 0.7. The number of particles in the APSO algorithm is set to 10, and the number of iterations is set to 500. The potential depth is 10, and the learning factor is $C1 = C2 = 2$. The spectrum width is 0.99. The data set in the experiment originated from the data set in the traveling salesman problem (TSP). In the performance analysis of the GA-BP, the research mainly analyzes the error curve, the prediction outcome and the comparison of the expected output. The research compares the performance of the GA-BP, tradition BP and the APSO-BP, and uses the same function to train the three algorithms. The number of iterations and the mean square error (MSE) are shown in Figure 5.

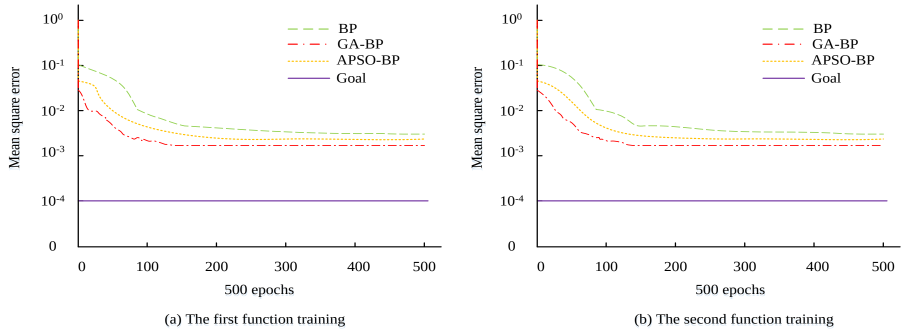


Figure 5: Iteration times and error curve

Figure 5 (a) and Figure 5 (b) display the number of iterations and MSE of the two functions used by the BP, GA-BP, and APSO-BP algorithms. In Figure 5(a), among the three algorithms, GA-BP had the fastest convergence speed and reached a stable state when the number of iterations was 130. At this time, the MSE of the GA-BP algorithm was the lowest, which was 0.00323. The BP neural network had the lowest convergence speed and reached a stable state when the number of iterations was 300. At this time, the MSE of the BP neural network was the highest, which was 0.00973. In Figure 5(b), the training times of the three algorithms were roughly consistent with the error curve. Among the three algorithms, the GA-BP algorithm had the fastest convergence speed and the lowest MSE after stabilization. There was still a gap between the MSE and the target value. Therefore, the performance of the algorithm can be optimized. The lower the MSE, the higher the accuracy of the algorithm. Therefore, from the MSE dimension, the performance of the GA-BP is best. This algorithm has higher accuracy in predicting data sets. The results show that the strong search ability of GA improves the weight and threshold of BP, improves convergence speed, and makes the MSE of GA-BP algorithm smaller than that of BP. In addition to MSE, the MAE and the maximum absolute percentage error (MAPE) can also be used as the index for assessing the performance of the algorithm. In the training of the three algorithms, the MAE and MAPE are shown in Figure 6.

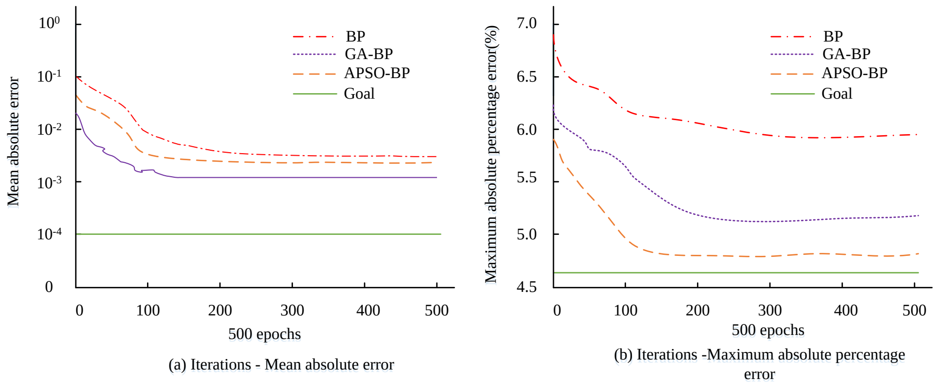


Figure 6: MAE and MAPE curves

Two sub-graphs in Figure 6 show the MAE and MAPE of the three algorithms during the training process, respectively. From Figure 6(a), the GA-BP had the fastest convergence speed among the three algorithms, and the MAE tended to be stable at 0.00152 when the iteration was 135. The convergence speed of the APSO-BP algorithm was second only to that of the GA-BP. For the APSO-BP, when the number of trainings was 180, the MAE tended to be stable, which was 0.00635. When the number of trainings was 250, the MAE tended to be stable, which was 0.00817. From Figure 6(b), the GA-BP algorithm had the fastest convergence speed among the three algorithms. The MAPE tended to be stable at 4.8% when the training times were 135 times. The convergence speed of the APSO-BP was the second. For the GA-BP, when the training times were 210, the MAPE tended to be stable, at 5.3%. The BP neural network had the slowest convergence speed. When the training times were 310, the MAPE tended to be stable at 6.1%. The results show that the GA-BP algorithm can solve the local minimum value, thus reducing the MAE value and MAPE value of the BP. From the above outcomes, it can be concluded that among the three algorithms, the GA-BP algorithm has better performance than the other two algorithms, but its MAE and MAPE have not yet reached the target value, and further improvements are necessary. To further compare the errors of each algorithm, the three algorithms after training are applied to the same training samples. The comparison of the prediction errors is shown in Figure 7.

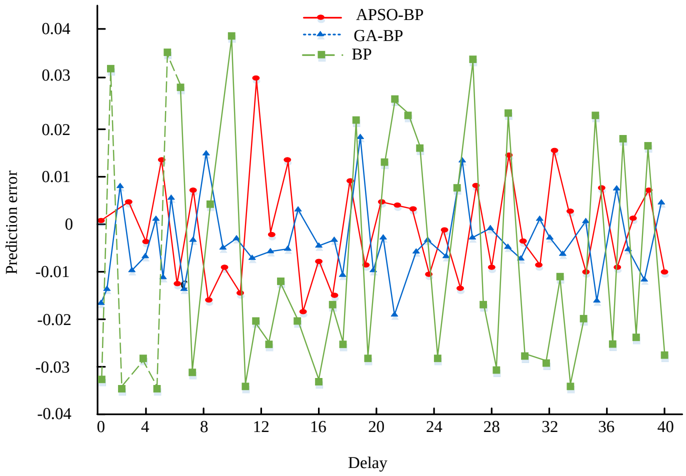


Figure 7: Prediction error of three algorithms

Figure 7 shows the prediction errors of the three algorithms in the training samples. In Figure 7, GA-BP algorithm predicted 40 samples more accurately. It is a prediction hit when the prediction error was within ± 0.015. Therefore, the hit rate of GA-BP algorithm was the highest among the three algorithms, which was 90%. The maximum error value of GA-BP algorithm was 0.019, which was lower than the maximum error value of 0.039 for BP and 0.028 for APSO-BP. The GA-BP has the highest hit rate and the lowest maximum error value among the three algorithms. From the perspective of the prediction error dimension, the performance of the GA-BP is the best among the three algorithms. The results show that applying the scalability of GA can reduce the error value in BP neural network. To compare the actual performance of the three algorithms, in addition to applying the three algorithms to the training samples for prediction, they are also applied to the test samples for prediction. The predicted outcomes are compared with the expected outcomes. The predicted and expected outcomes are shown in Figure 8.

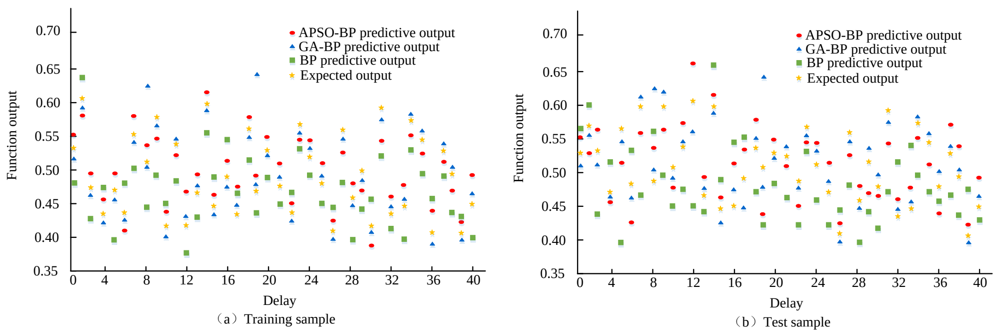


Figure 8: Predicted outcomes and expected outcomes of three algorithms

Figure 8 (a) and (b) are the scatter plots of the prediction outcomes and expected outcomes of the three algorithms in training samples and testing samples. In Figure 8 (a), among the three algorithms, the prediction outcome of GA-BP algorithm was the closest to the expected outcome. The difference between the predicted outcomes and the expected outcomes of the GA-BP algorithm was relatively stable, which showed that the GA-BP algorithm had the best prediction performance in the training samples among the three algorithms. From

Figure 8 (b), the prediction effect of the GA-BP algorithm was the best in the testing samples, the APSO-BP algorithm was the second, and the BP was the worst. It shows that GA uses the objective function, thereby improving the prediction accuracy of the GA-BP. The GA-BP algorithm has the best prediction performance among the three algorithms in the testing sample. Summarizing the performance of the above three algorithms in PE, MSE, MAE, and MAPE, GA-BP algorithm has the best performance. Using this algorithm to evaluate the quality of crew training and teaching has higher accuracy, which can better predict the shipping safety. After the GA-BP model is completed, the model is empirically analyzed to find the factors that have the greatest impact on shipping safety among the factors affecting crew education and training. The model analysis outcomes are shown in Table 3.

Table 3: Shipping safety assessment outcomes

| Primary index | Indicator Code | Indicator code | Output outcomes |
|---|---|---|---|
| Crew factor | Family environment background | Z1 | 0.85 |
| | education level | Z2 | 0.91 |
| | Psychological quality | Z3 | 0.92 |
| | Physical quality | Z4 | 0.90 |
| | Adaptability | Z5 | 0.93 |
| Education and training institutions | Meet the requirements of the competent authority | Z6 | 0.68 |
| | Teacher level | Z7 | 0.76 |
| | Condition of facilities and equipment | Z8 | 0.55 |
| | Training scale | Z9 | 0.91 |
| | Training cycle | Z10 | 0.93 |
| | Operation of quality system | Z11 | 0.75 |
| | market demand | Z12 | 0.63 |
| Shipping company | Information integration processing | Z13 | 0.66 |
| | Crew entry standard settings | Z14 | 0.77 |
| | Feedback of new ship technology | Z15 | 0.56 |
| | Demand for production safety | Z16 | 0.63 |
| | Crew management level | Z17 | 0.72 |
| Competent authority | Evaluation of crew training effect | Z18 | 0.48 |
| | Daily supervision service | Z19 | 0.53 |

The scores of indicators Z2, Z3, Z4, Z5, Z9, and Z10 were all above 0.90. It can be seen that these indicators are most relevant to shipping safety. In the subsequent crew education and training, more attention should be paid to these indicators. By strengthening these indicators, the overall quality of the crew is improved, thereby reducing shipping risks and improving shipping safety.

# 5 Discussion

This study conducted performance comparison experiments on GA-BP algorithm, BP, and APSO-BP algorithm. The experimental results showed that the MSE value of the GA-BP algorithm reached stable at 0.00323 after 130 iterations, However, the MSE value of the BP neural network did not reach the stable value until the iterations were 300, and the value was the highest at 0.00973 among the three algorithms. Due to the advantage of GA, the weights and thresholds in the neural network algorithm are adjusted and the convergence rate is optimized. The mean squared error value of GA-BP algorithm was less than that of BP. This result is similar to the study conducted by Wei et al. [21]. Later, the MAE, MAPE and error values of the three algorithms were compared. The results showed that the GA-BP algorithm converged the fastest, and the MAE, MAPE and maximum error value of the algorithm were 0.00152, 4.8% and 0.019 respectively. The convergence rate of APSO-BP algorithm was less than that of GA-BP algorithm, and the MAE, MAPE and error value of this algorithm were 0.00635, 5.3% and 0.028, respectively. However, the BP showed the slowest convergence rate, and the maximum MAE, MAPE and error values were 0.00817, 6.1% and 0.039, respectively. The reason for this result may be that the GA in GA-BP algorithm can solve the problem that the initial value difference of BP causes the local minimum value of training, thus reducing the MAE, MAPE, and error values of the algorithm. The result coincides with results conducted by Wang [22]. The study also compared the prediction results and expected results of the three algorithms in practical application. The comparison results showed that the difference between the predicted results and the expected results was the smallest, followed by APSO-BP algorithm, while the BP had the largest difference between the expected results. The GA utilized objective function to reduce error factor, thus improving the prediction accuracy of GA-BP algorithm. This result is similar to the Zhang result, as shown in [23]. Finally, An empirical analysis was conducted on the education and training quality evaluation model based on the GA-BP algorithm. By scoring the indicators, the factors that have the greatest impact on crew education, training, and shipping safety are identified. The experimental results showed that the educational level, psychological quality, physical quality, adaptability, training scale and training cycle had the greatest influence on shipping safety. Therefore, the shipping safety can be improved by strengthening the training of the above indicators. This result is identical to that of the results cunducted by Nopas [24]. From the above results, it can be seen that the overall prediction performance of GA-BP algorithm is significantly better than other algorithms. The influence index of crew training quality on shipping safety can be accurately obtained through this algorithm.

# 6 Conclusion

With the increase of maritime business, more maritime accidents have occurred, and shipping safety has been widely concerned. There is a correlation between the shipping safety and the quality of crew education and training, but the relationship is not particularly clear. At present, there is also a lack of research on this issue. To solve the problem, the GA was used to adjust the parameters of the BP to obtain the optimized GA-BP algorithm. The relevant factors in the crew education and training were calculated by this algorithm, and the correlation between the GA-BP algorithm and the shipping safety was obtained. To test the performance of the GA-BP algorithm, it was compared with tradition BP and APSO-BP algorithm from multiple dimensions. The hit rate of GA-BP algorithm was 90%, the maximum error value was 0.019, the MAE was 0.00152, the MSE was 0.00323, and the MAPE was 4.8%, which were better than APSO-BP algorithm and BP. This outcome shows that the GA-BP has the best performance, which has higher accuracy in predicting samples. In addition, the study also conducted an empirical analysis for the model. The outcomes showed that the output outcomes of education level, psychological quality, physical quality, adaptability, training quality, and training cycle were 0.91, 0.92, 0.90, 0.93, 0.91, and 0.93, respectively. The outcomes illustrate that these indicators in crew training that have the greatest impact on shipping safety. By improving these indicators, shipping safety can be improved. This study demonstrates that in actual crew training, the education level, physical quality, adaptability, and psychological quality of crew members should be improved, and educational institutions should pay attention to the quality and duration of training. By improving the comprehensive abilities of crew members, shipping safety can be improved. Although the GA-BP algorithm has high prediction accuracy, it is far from the expected goal. The follow-up research direction is to establish a neural network model more suitable for shipping safety prediction.

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# References

[1] B. Debeelde, E. Tanghe, M. Yusuf, D. Plets, W. Joseph, "Radio channel modeling in a ship hull: path loss at 868 MHz and 2.4, 5.25, and 60 GHz," IEEE and Wireless Propagation Letters, vol. 20, no. 4, pp. 597-601, 2021. https://doi.org/10.1109/LAWP.2021.3058439

[2] I. Subotič, "3G, HSPA AND 4G LTE network reliability and achievable internet speeds on airborn aircraft up to 10.000 FT above ground level," Informatica, vol. 47, no. 5, pp. 95-110, 2023. https://doi.org/10.31449/inf.v47i5.4513

[3] S. Choi, and J. Kim, "Meta-analysis on the effectiveness of airline crew training and education," Journal of Tourism Management Research, vol. 24, no. 3, pp. 749-766, 2020. https://doi.org/10.18604/tmro.2020.24.3.34

[4] X. Zhu, J. Li, Q. Liu, W. Yu, S. Li, J. Zhao, Y. Dong, Z. Zhang, H. Zhang, and S. Lin, "Use of a BP neural network and meteorological data for generating spatiotemporally continuous LAI time series," IEEE Transactions on Geoscience and Remote Sensing, vol. 99, pp. 1-14, 2021. https://doi.org/10.1109/TGRS.2021.3095535

[5] Q. Kuang, "Image pattern recognition algorithm based on improved genetic algorithm," Journal of Physics Conference Series, vol. 182, no. 3, pp. 032038, 2021. https://doi.org/10.1088/1742-6596/1852/3/032038

[6] W. Zhu, H. Wang, and X. Zhang, "Synergy evaluation model of container multimodal transport based on BP neural network," Neural Computing and Applications, vol. 33, no. 2, pp. 4087-4095, 2021. https://doi.org/10.1007/s00521-020-05584-1

[7] B. Shao, C. Ni, J. Wang, and Y. Wang, "Research on venture capital based on information entropy, BP neural network and CVaR model of digital currency in Yangtze River delta," Procedia Computer Science, vol. 187, pp. 278-283, 2021. https://doi.org/10.1016/j.procs.2021.04.063

[8] Y. Liu, X. Wang, X. Zhu, and Y. Zhai, "Thermal error prediction of motorized spindle for five-axis machining center based on analytical modeling and

BP neural network," Journal of Mechanical Science and Technology, vol. 35, no. 1, pp. 281-292, 2021. https://doi.org/10.1007/s12206-020-1228-7

[9] H. Xi, Z. Li, J. Han, D. Shen, N. Li, Y. Long, Z. Chen, L. Xu, X. Zhang, D. Niu, H. Liu, "Evaluating the capability of municipal solid waste separation in China based on AHP-EWM and BP neural network," Waste Management, vol. 139, pp. 208-216, 2022. https://doi.org/10.1016/j.wasman.2021.12.015

[10] K. X. Zhou, W. H. Lin, J. K. Sun, J. Zhang, D. Zhang, X. Feng, Q. Liu, "Prediction model of end-point phosphorus content for BOF based on monotone-constrained BP neural network," Journal of Iron and Steel Research International, vol. 29, no. 5, pp. 751-760, 2022. https://doi.org/10.1007/s42243-021-00655-6

[11] J. Zhou, F. Ding, J. Yang, Z. Pei, C. Wang, and A. Zhang, "Navigation safety domain and collision risk index for decision support of collision avoidance of USVs," International Journal of Naval Architecture and Ocean Engineering, vol. 13, no. 3, pp. 340-350, 2021. https://doi.org/10.1016/j.ijnaoe.2021.03.001

[12] P. Nosov, S. Zinchenko, A. Ben, Y. Prokopchuk, P. P. Mamenko, I. Popovych, V. Moiseienko, and D. Kruglyj, "Navigation safety control system development through navigator action prediction by data mining means," Eastern-European Journal of Enterprise Technologies, vol. 2, no. 110, pp. 55-68, 2021. https://doi.org/10.15587/1729-4061.2021.229237

[13] N. Shilov, "Recommender system for navigation safety: requirements and methodology," TransNav the International Journal on Marine Navigation and Safety of Sea Transportation, vol. 14, no. 2, pp. 405-410, 2020. https://doi.org/10.12716/1001.14.02.18

[14] N. Hasanspahi, V. Frani, I. Rudan, and L. Maglic, "Analysis of navigation safety regarding tankers in narrow waterways," Journal of Maritime & Transportation Science, vol. 55, no. 1, pp. 201-217, 2019. https://doi.org/10.18048/2018.00.13

[15] Y. Zhou, Y. Wang, X. Wen, and C. Han. "Application of BP neural network in efficiency prediction of oilfield mechanized mining system," Journal of Failure Analysis and Prevention, vol. 22, no. 2, pp. 658-665, 2022. https://doi.org/10.1007/s11668-022-01360-6

[16] S. Xu, Z. Lin, G. Zhang, T. Liu, X. Yang, "A fast yet reliable noise level estimation algorithm using shallow CNN-based noise separator and BP network," Signal Image and Video Processing, vol. 14, no. 1, pp. 1-8, 2020. https://doi.org/10.1007/s11760-019-01608-z

[17] H. Xi, Z. Li, J. Han, D. Shen, N. Li, Y. Long, Z. Chen, L. Xu, X. Zhang, D. Niu, H. Liu, "Evaluating the capability of municipal solid waste separation in China based on AHP-EWM and BP neural network," Waste Management, vol. 139, pp. 208-216, 2022. https://doi.org/10.1016/j.wasman.2021.12.015

[18] X. Zhang, "Analysis of financial market trend based on autoregressive conditional heteroscedastic model and BP neural network prediction," Journal of Intelligent and Fuzzy Systems, vol. 39, no. 4, pp. 5845-5857, 2020. https://doi.org/10.3233/JIFS-189060

[19] S. Samanta, A. Ojha, B. Das, and S. K. Mondal, "A profit maximisation solid transportation problem using genetic algorithm in fuzzy environment," Fuzzy Information and Engineering, vol. 4, pp. 1-18, 2021. https://doi.org/10.1080/16168658.2021.1915454

[20] W. F. Li, "Reactive power optimization of a power system based on genetic algorithm," Electric Switchgear, vol. 52, no. 4, pp. 47-49, 2014. https://doi.org/10.3969/j.issn.1004-289X.2014.04.014

[21] W. Wei, R. Cong, Y. Li, A. A. Daniel, C. Yang, and Z. Chen, "Prediction of tool wear based on GA-BP neural network," Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, vol. 236, no. 12, pp. 1564-1573, 2022. https://doi.org/10.1177/09544054221078144

[22] L. Wang, and X. Bi, "Risk assessment of knowledge fusion in an innovation ecosystem based on a GA-BP neural network," Cognitive Systems Research, vol. 66, no. 8, pp. 201-210, 2021. https://doi.org/10.1016/j.cogsys.2020.12.006

[23] H. Zhang, and Z. Tian, "Failure analysis of corroded high-strength pipeline subject to hydrogen damage based on FEM and GA-BP neural network," International Journal of Hydrogen Energy, 47(7): 4741-4758, 2022. https://doi.org/10.1016/j.ijhydene.2021.11.082

[24] D. Nopas, C. Ueangchokchai, and W. Meepan, "The study of the training platform towards thailand's international airlines cabin crew during the pandemic of COVID-19," Higher Education Studies, vol. 13, no. 3, pp. 45-53, 2023. https://doi.org/10.5539/hes. v13n3p45